ISBI 2015 – Machine Learning for Neuroimaging Course

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Motivation

In recent years, the application of machine learning techniques to neuroimaging data has increased substantially and lead to many new analytic procedures, and sometimes new neuroscientific concepts. *Pattern recognition* approaches consist of a whole family of tools coming from the machine learning community, that borrow from statistics and engineering, which have been adapted to investigate neuroscience questions, but also in medical settings, to address diagnosis problems. Depending on the research question, experimental design and imaging modality, it is important to know how to draw reliable conclusions. The set of relevant machine learning techniques for neuroimaging is conditioned by neuroimaging data constraints, such as the small sample size or the relatively low signal-to-noise ratio of the data in the case of functional neuroimaging. Another noticeable characteristic of the application of machine learning tools to neuroimaging problems is that black-box approaches are not well suited, since the practitioner ultimately wants to confirm some hypotheses on the brain structures involved in a given cognitive process or a disease.

The course will focus both on subject and/or patient classification (for cognitive and clinical applications) and on regression issues. The usual functional and structural MRI modalities will be covered but the presentations will consider other types of data such as PET, EEG/MEG and network metrics. After introducing the theoretical foundations of pattern recognition in neuroimaging, the subsequent lectures will introduce methodological aspects specific to applying the approaches to anatomical and functional imaging modalities. All the concepts introduced will be illustrated with actual examples rom neuroimaging.

It is expected that participants already have passing knowledge of machine learning/pattern recognition. At the end of the course, participants should have a broad understanding of some core pattern recognition approaches, how to apply these tools to their data to address neuroscientific questions, and how to interpret the outcomes of these analyses and draw reliable conclusions.

Specific goals

The course is organized such that the participant acquire knowledge about
1. the main concepts of machine learning in the light of neuroimaging constraints.
2. the problem of discriminative feature identification and its link to estimation problems.
3. the crucial impact of quality check to perform meaningful analysis of the data.
4. the implementation of relevant priors to compensate for the shortage of data.
5. the usefulness and issues regarding the use of recent computer vision approaches (e.g. deep neural nets)
6. some of the various pattern recognition software available

Outline

The course is organized as follows:

- Part I Pattern recognition for Neuroimaging (45'): BT + JA
- questions 15'
- Part II Machine Learning for anatomical Neuroimaging: JA (60')
- question 15'
- break 30'
- Part III Machine Learning for functional Neuroimaging: BT (60')
- question 15'

Part I Pattern Recognition

Goal: Revise certain general concepts of pattern recognition while emphasizing the particular constraints related to neuroimaging.

* Introduction
  - Classification and Regression
  - Curse of Dimensionality
* Generalization of learned models across datasets
  - Cross-Validation
  - Accuracy Measures
  - Parameter Tuning (via cross-validation)
* Overview of the main methods
  - Simple Methods: Naive Bayes, Linear Discriminant Analysis
  - Kernel Methods: Support-Vector Machines, Gaussian Processes
  - Basic Regularization Methods (some advanced methods will be covered in the functional neuroimaging part)
* Model Averaging
  - decision trees and Random Forests
  - Boosting & Bagging
* Tools: scikit-learn, pronto, nilearn, pymvpa

Part II Machine Learning for anatomical Neuroimaging

Goal: Understand how computational anatomy tools and concepts map to machine learning settings.

II.A Introduction
- Why apply pattern recognition to structural MRI?
- Common ways to represent anatomical features.
- No Free Lunch and prior knowledge.
- Dimensionality reduction.

II.B Geometric Morphometrics
- Early univariate morphometry.
- Early multivariate morphometry.
- The morphometrics "revolution" (landmarks).
- Allometric relations.
- Automated shape estimation.

II.C Similarity between brains
- Distances between anatomies.

- Non-linear distances (manifolds).
- Image registration for measuring distances.
- Tangent space representations.
- Scalar momenta.
- Empirical examples.

II.D Conclusion: What next?
Speculation about the future: semi-supervised approaches, dealing with uncertainty in labels, possible role of deep learning, etc.

Part III Machine Learning for functional Neuroimaging

Goal: Go from standard *multivariate pattern analysis* settings to proper multivariate models of functional neuroimaging data.

Introduction: The neuro-vascular coupling. The BOLD signal only indirectly reflects neural activity.

III.A Machine learning for cognitive neuroimaging : decoding and encoding models
- Analysis setting: setting of standard fMRI/MEG experiments, limitations of the data (resolution, SNR, artifacts)
- encoding models : mapping stimulus features to brain activations
    - principle, choice of the loss function, illustration on vision
- decoding models : predicting behavior from activation maps / “Vanilla MVPA”
    - principle, classification/regression, illustration on vision
- Conclusion: Impact of HRF model on encoding/decoding models

III.B Region selection and Identification:
- Choose a spatial model for MVPA
    - whole-brain analysis
    - ROI based analysis
    - Searchlight
- Identification : Recover the truly associated features -- the hard problem
    - Formulation of the problem; link with sparsity
    - Ill-posedness of the problem: violation of the standard recovery condition; smoothness and clustering

III.C. Tailored priors for brain activity decoding
- The relevant priors : smoothness, sparsity, analysis sparsity
    - Their role in prediction and identification
- A generic framework to regularize estimates with the relevant priors
    - Engineering of penalized regression models
- Pitfalls and issues
    - Convergence issues, parameter setting, computation time, lack of good software.

III.D Toward Big data in cognitive neuroimaging
- Multi-class problems in cognitive neuroimaging: meta-analyses
    - Overcome the limitations of dataset-specific inference
- Mapping terms to activation maps
    - Problem setting, current solutions
- Toward deep learning methods in functional neuroimaging
    - Pros and cons. Illustration on vision.